Condition-based Monitoring as a Robust Strategy Towards Sustainable and Resilient Multi-Energy Infrastructure Systems

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Abstract

A resilient energy infrastructure system is exceptionally imperative to ensure uninterrupted energy supply to support the nation's economic growth. The resilience capability in energy infrastructures can be realized through effective planning decisions and maintenance strategies by implementing the condition-based monitoring (CBM) approach. CBM minimizes the unplanned downtime of a system by monitoring the system's health status in real-time and predicting upcoming failures. Thus, the planned maintenance can be performed before failures occur. With advancements in data analytics, conventional CBM methods have been enhanced with modern artificial intelligence algorithms to improve the prediction accuracy. This paper comprehensively evaluates the importance of CBM as a robust strategy to enhance energy infrastructure resilience. The vulnerabilities of energy infrastructure and current advancements in data-driven CBM methods are detailed. Furthermore, this survey equip energy infrastructure stakeholders and practitioners with CBM knowledge in managing unforeseen disaster risks, such as power failures due to adverse weather conditions.

Keywords: Resilience, sustainable, energy, infrastructure, condition-based monitoring, machine learning

1. Introduction

Energy infrastructures system plays a vital role as a backbone to other critical infrastructures (CIs) such as the transportation system sector, communication sector, defense industrial base sector, emergency services sector, or financial service sector (Praminta et al., 2020). The common energy sources used in the United States can be categorized as primary and secondary. Primary energy sources include non-renewable (petroleum, natural gas, coal, and nuclear) and renewable (solar, wind, hydro, geothermal, and biomass) energy. Secondary energy sources, for example electricity and heat, cannot be mined or harvested, instead they are produced or converted from primary energy sources. Based on the April 2022 monthly energy review data source from the U.S. Energy Information Administration (EIA), the amount of energy consumed by U.S. consumers from different energy sources in 2021, with petroleum and natural gas alone making up about 68% of the overall energy consumption and renewable energy only accounting for 12% (*U.S. Energy Information Administration*, 2022). The 2021 EIA data also hinted that 96% of the secondary energy source, utility-scale electric power generation, is sold to other sectors such as transportation, iAndustrial, commercial, and residential.

This multi-energy infrastructure system, often referred to as energy infrastructure, governs the generation and distribution of electricity from various energy sources to end-user customers. The input-output of complex generating and distributing energy operations is not always efficient. The electrical power sector suffers from 65% of energy losses associated with energy generation, conversion, transmission, and distribution and only 35% accounts for electric retail sales (*U.S. Energy Information Administration*, 2022). To complicate things, the performance of energy infrastructure systems significantly affects the other CIs due to the inherent dependency and interdependency property of networked systems. This dependability among CIs can make the energy systems vulnerable to unexpected disruptions, and the effect may propagate to other dependent infrastructure systems and vice versa, causing cascading failures (Ekic et al., 2022).

As climate and disruption risk increases, extreme weather conditions that cause energy systems disturbances have also significantly increased over the past years. For example, in February 2021, the state of Texas suffered a major power crisis due to a severe winter storm known as the Texas freeze. It had left more than 4 million people without power, heat, and running water for several days due to the lack of the state's electricity grids and pipeline preparations, causing estimated economic losses of $130 billion in Texas (Busby et al., 2021; Cohen, 2021b). Moreover, unexpected natural disasters and events, such as hurricanes and terrorist attacks, can threaten the operation of energy infrastructures. Hurricane Ida in 2021 eliminated about 94% of offshore gulf oil production and caused a power cut in one million homes across Louisiana and Mississippi states (Cohen, 2021a; Geman & Freedman, 2021). In addition to a significant natural disaster event, energy infrastructures can also fail due to deterioration of the network caused by intrinsic aging, component failures, and poor maintenance.

To mitigate the impacts of any unwanted events on the energy supply, the energy infrastructure systems need to be disaster resilient. Resilience is a concept that describes the ability of a system to adapt to any disruptive events and continue functioning after the event (Wen et al., 2020). Resilience is also related to the reliability and recovery of a system after an attack, disturbance, or failure (Ayyub, 2020; Yodo & Wang, 2016). One fundamental aspect of resilience is the recovery or restoration ability of the system to cope with unavoidable risks (Zorn & Shamseldin, 2015). Recovery planning for potential future shortcomings is essential for developing a resilient multi-energy infrastructure system amid increasing climate and disaster risks (Afrin & Yodo, 2022a). Moreover, integrating resilience enhancement in the existing energy infrastructure is also beneficial to ensure system sustainability in the long run (Ayyub, 2015; Lounis & McAllister, 2016).

To improve the resilience of energy infrastructures, the timely restoration of critically damaged components should be achieved (Afrin & Yodo, 2019). Maintenance activity is proven to minimize the total completion time of restoration (Mosheiov & Sarig, 2009; Yang et al., 2011). Condition-based monitoring (CBM) is a widely practiced predictive maintenance approach in operation and maintenance (Helsen et al., 2015; Stetco et al., 2019). CBM involves observing the health of system components in real-time and identifying any operational changes that can indicate potential component failures. It further helps identify weaker or vulnerable sub-systems or components and work on those vulnerable elements before an upcoming natural disaster or extreme weather conditions. Common CBM approaches include analyses of specific measurements and operation attributes, such as vibration and temperature analysis, strain measurement, and acoustic emissions. Predicting potential faults in the system through CBM can reduce maintenance costs and unnecessary downtime, leading to improved resilience characteristics in a system. This paper will focus only on advances in CBM efforts in shaping energy infrastructure resilience.

CBM also benefitted from connection paradigms where it should be capable of gathering information from multiple on-site sensors, preferably in a real-time scenario. The Internet of Things (IoT) approaches have facilitated the advancements of CBM via remote and distributed sensing technology to increase the performance of energy infrastructure through effective information management and analysis (Karad & Thakur, 2021). The IoT-based CBM in energy infrastructure has evolved from the traditional energy infrastructure towards the concept of smart or intelligent energy infrastructures for sustainable cities (Renugadevi et al., 2021). To ensure the proper functioning of these complex energy infrastructures, all essential parameters must be continuously monitored and maintained over time (Karad & Thakur, 2021). In recent years, advancements in sensors and signal processing, big data analytics, artificial intelligence (AI), machine learning (ML) applications, and computational capabilities have increased the opportunities for CBM to be readily integrated into multi-energy infrastructure planning and decisions (Blatter, 2021). Thus, CBM should be adaptively incorporated into the existing and new multi-energy infrastructure to combat future weather-related disaster risks and uncertainty and to ensure long-term sustainability.

In their own respective field, CBM, AI/ML approaches, and resilience concepts have been applied separately to improve energy infrastructure. However, there are still some knowledge gaps between the expertise from these individual fields to develop a multidisciplinary and holistic framework that incorporates all these advancements. AI/ML approaches originated from data science. Although the CBM concept is quite familiar to all of those who are even marginally involved with maintenance and management duties, how CBM and AI/ML advancements can be holistically integrated to develop a sustainable and resilient energy infrastructure is still lacking in practice. The opportunities to integrate CBM to realize sustainable and resilient concept in energy infrastructure has grown with the advancement of AI/ML applications in recent years. CBM is often related to reliability instead of sustainability and resilience. To fill this knowledge gaps, the detail of how CBM can be a potential adaptive pathway for resilient energy infrastructure will be detailed throughout this paper. Hence, the novelty of this paper lies in the notion of integrating advanced CBM to realize the resilience concept in energy infrastructure. As a broader impact, this paper also advocates for resilient and sustainable energy and other critical infrastructure developments by helping readers and/or practitioners understand the underlying influence of CBM on resilience development.

Additionally, this paper aims to (1) present a survey on CBM methods in energy sectors, focusing on the current data-driven methods, (2) highlight the role of CBM in the resilience enhancement of energy infrastructures, and (3) present future research opportunities for building resilient critical infrastructures via CBM. The sections in this manuscript are organized as follows. Section 2 presents an overview of the energy infrastructure's complex structure and operations that lead to its vulnerabilities and the role of resilience in overcoming the vulnerabilities. Section 3 discusses the impacts of CBM on resilience enhancements and reviews the current state of the art of CBM approaches. In Section 4, opportunities, challenges, and potential future research directions are identified.

2. Energy Infrastructures Systems

Energy infrastructure system are in charge of producing, converting, and transporting energy to the end-users via millions of miles of electric power grids and/or oil and gas pipelines (Wu & Wang, 2021). To support the functioning of our modern societies. These large-scale energy networked systems have an incredibly complex infrastructure and operations. The complex interactions and dependencies between multiple components, sub-systems, and the entire energy network systems can be vulnerable to failures due to unexpected disturbances or unplanned maintenance activities. This section discusses the inherent complexity of energy networks, common vulnerability scenarios, and what it takes for this energy infrastructure to become resilient against future uncertainty.

The information presented in this section is related to the existing advances of energy infrastructure systems and was collected via a hybrid survey approach introduced by (Wohlin et al., 2022). This hybrid survey approach combines database search (mainly from google scholar with the specific keywords) and snowballing approach. For example, to develop Section 2.1, the keywords used in the database search were “energy networks,” “energy infrastructure,” or “energy system,” combined with phrases such as “properties,” “characteristics,” or “complexity.” Literature from five years ago (from 2017) was collected and screened further based on the related content to the presented section. The snowballing approach was further applied to a specific topic and resulted in minor fundamental research literature included in this survey prior to 2017. The same survey approach was employed to develop the rest of Section 2 and Section 3.

2.1 Complex Characteristics of Energy Infrastructure

As the demand for energy increases due to population growth and the scarcity of non-renewable energy sources, integrating multiple energy sources is inevitable to achieve a reliable and sustainable energy supply. Different energy networks (electricity, gas, heating/cooling) are initially designed with the objective that they can be operated independently (Poudineh, 2022). Existing energy infrastructures are often retrofitted with the new infrastructure system to support growing demands, resulting in the holistic energy network's expansion of scale and complexity (Yodo et al., 2017). The diverse operations involving multiple stakeholders in energy networks have inevitably resulted in multi-layer, multi-vector, and multi-dimension energy networks (Hosseini et al., 2020).

Multi-layer energy networks. Energy networks comprise different energy infrastructures, including multi-energy sources, multi-consumers, energy conversion devices, energy storage, and transport systems, to name a few (Bruckner et al., 2014). Due to the interdependencies of connections, energy infrastructure is often represented with the graph or network theory approach, which consists of a collection of nodes and links, as shown in Figure 1. The nodes can represent energy sources, transmission points, or customers, and the links represent the energy flow lines or, in general terms, any connections between the nodes. Figure 1(a) presents a partial energy infrastructure network in North Dakota with power plants as nodes and electricity transmission lines and gas pipelines as the links. The combination of nodes and links resulted in a networked structure.

Energy network structure can quickly become very complex as more entities of energy networks are considered. Figure 1(b) shows a general energy network structure in a three-layer network structure consisting of generation in the top layer, transmission and distribution in the middle layer, and the end customers in the bottom layer. There are many interconnected, diverse components between the boundary of each layer. Connections between the element do not only exist inside the system's or layer's perimeter but also outside the system boundary to establish relationships between layers.

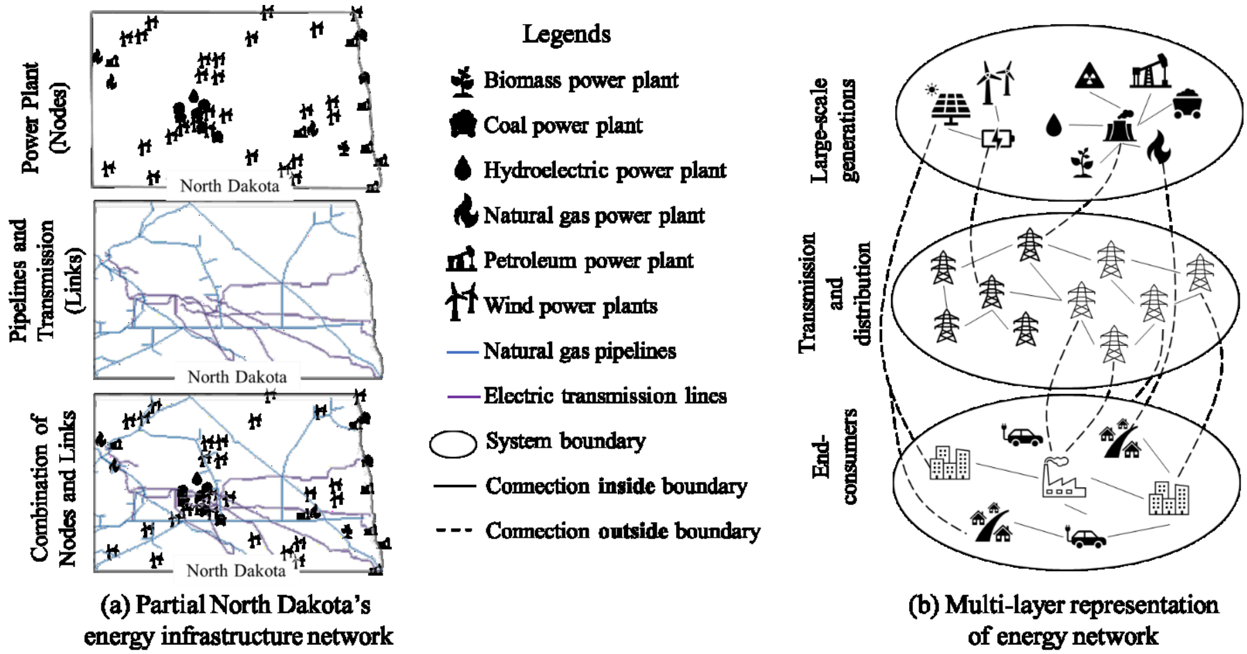

Figure 1: Multi-layer energy infrastructure network

This multi-layer network structure is a common approach adopted in energy structure modeling and analysis. Shafie-Khah and Catalão analyzed the behavior of electricity market participants with a stochastic multi-layer agent-based model consisting of wind power producers and plug-in electric vehicle consumers (Shafie-Khah & Catalão, 2014). Lombardi et al. applied multi-layer energy modeling to investigate the economic and environmental of heat-electricity integration strategies (Lombardi et al., 2019). Davoudi et al. proposed a multi-layer energy hub structure to address the interconnections between all the energy installations from the largest ones to study the optimal design of residential complex energy systems (Davoudi et al., 2022).

Multi-vector energy networks. Integrating multiple energy systems is beneficial in terms of the better utilization of the various energy sources and minimizing the dependencies on non-renewable energy sources. The adaptation of energy transmission from various energy subnetworks can occur through energy conversion sub-systems, including heat-only boilers (gas-to-heat), power plants (gas-to-power), cogeneration plants (gas-to-heat and power), heat pumps (power-to-heat), and technologies which convert electricity into fuel such as hydrogen and methane (power-to-gas). Moreover, renewable energy sources, such as wind, solar, hydro, ocean, geothermal, and biomass, can also be integrated into the main electricity grid. The efficient implementation of renewable energy within the existing power grid can reduce carbon emissions and have a vital role in improving the overall system's reliability and resilience. It is also seen as cost-effective as operational delays and capital expenditures are minimized. (Bagherian et al., 2021; Chauhan & Saini, 2014)

Goswami and Kreith have a comprehensive survey on advances in energy generation and conversion that covers non-renewable and renewable energy in their book (Goswami & Kreith, 2007).. Multiple individual energy networks interact mainly through energy conversion to provide optimal system management and services, resulting in multi-vector energy systems (Hosseini et al., 2020), also known as multi-carrier energy systems (Nazari-heris et al., 2020; O'Malley et al., 2020).

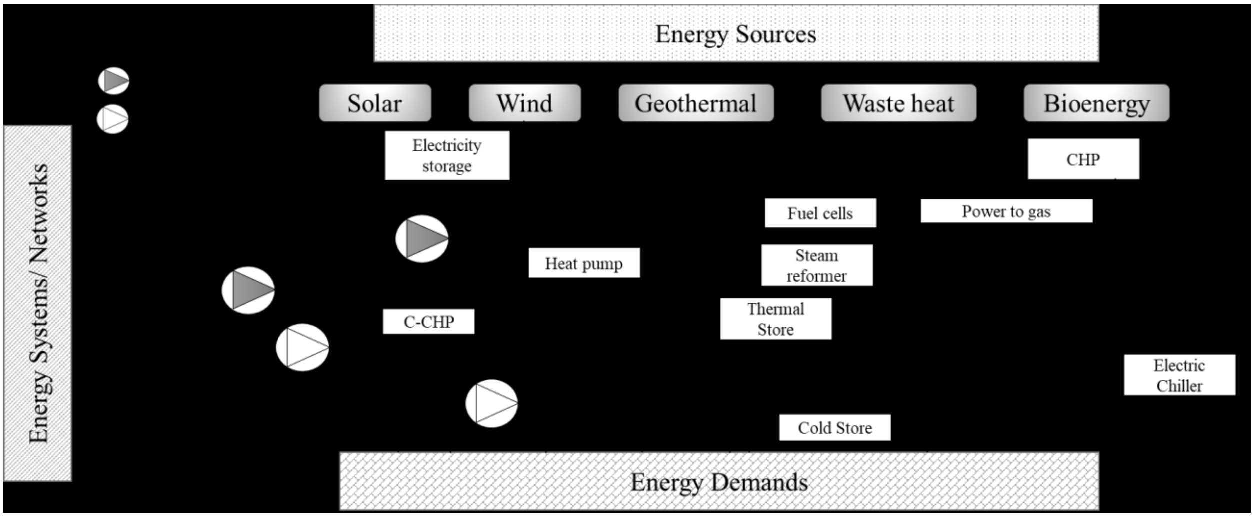

Figure 2: Multi-vector energy network representation adopted from (Abeysekera, 2016; Taylor et al., 2022)

Multi-vector energy network refers to an integrated multi-energy system with coupling components between multiple energy sources (solar, wind, geothermal, waste heat, or bioenergy) and various energy demands (Taylor et al., 2022). To fulfill these diverse demands, there are various integrated energy systems, such as power network to deliver electricity, and other energy conversion systems such as hydrogen, gas, heat, and cooling system. A representative of the two-dimension multi-vector energy structure is shown in Figure 2. The energy conversions between multiple energy sources, energy systems, and energy demands are based on the coupling components, such as compressors and pumps, denoted as a combined circle and triangle symbol in Figure 2. Gas compressors control the distribution of natural gas and require electricity to operate. These coupling components have grown into complex coupling systems with multiple integrations of various energy sources. Some examples are combined-cycle gas turbines (C-CGT), combined heat and power units (CHP), combined cooling, heat, and power systems (C-CHP), power to gas equipment, and heat pumps, as identified in Figure 2 (Hosseini et al., 2021).

The holistic analysis of a multi-vector energy network can be very challenging due to the complex technical integration of a multi-energy system with numerous controllable and uncontrollable parameters (Reynolds et al., 2018). Carradore and Turri developed a simulation environment of multi-vector energy networks focusing on electrical and thermal networks, which are coupled with distributed CHP units (Carradore & Turri, 2009). Multi-objective optimization based on a mixed-integer programming approach has also been proposed to optimize the design and operation of integrated multi-vector energy networks (Samsatli & Samsatli, 2018). Hosseini et al. reviewed various strategies to achieve operational analysis and optimal dispatch, and optimal planning for multi-vector energy systems (Hosseini et al., 2020)

Multi-dimensional energy network. The functioning of energy networks does not only depend on the internal components and operations, but also contingent on other external factors such as resource availability, economic, geopolitical, or security (Min et al., 2021). These external factors influencing the energy network operation have resulted in a multi-dimensional model and increased complexity in developing a holistic energy infrastructure analysis. The representative figures are shown in Figure 3. Energy infrastructure sources depend heavily on non-renewable resources such as coal or petroleum or renewable energy sources such as wind or solar energy. Therefore, the resource availability dimension should be considered in addition to analyzing the internal components and operations of energy infrastructure.

With the integration of the Internet of Things (IoT), energy infrastructure operations depend on support from communication and technology systems, resulting in the requirement that the Information Technology (IT) dimension should be included in the overall analysis. Additionally, the economic dimension deals with price and demand adjustment, operational profit and loss, and some strategies to account for inflation if present (Bhattacharyya, 2019). Energy infrastructure also has been associated with environmental dimensions due to the availability of energy sources and the operation of energy networks often related to climate change and pollution. Geopolitical dimensions may include different geographical regions and governmental policies or strategies, for example, trade policy between countries (Blondeel et al., 2021).

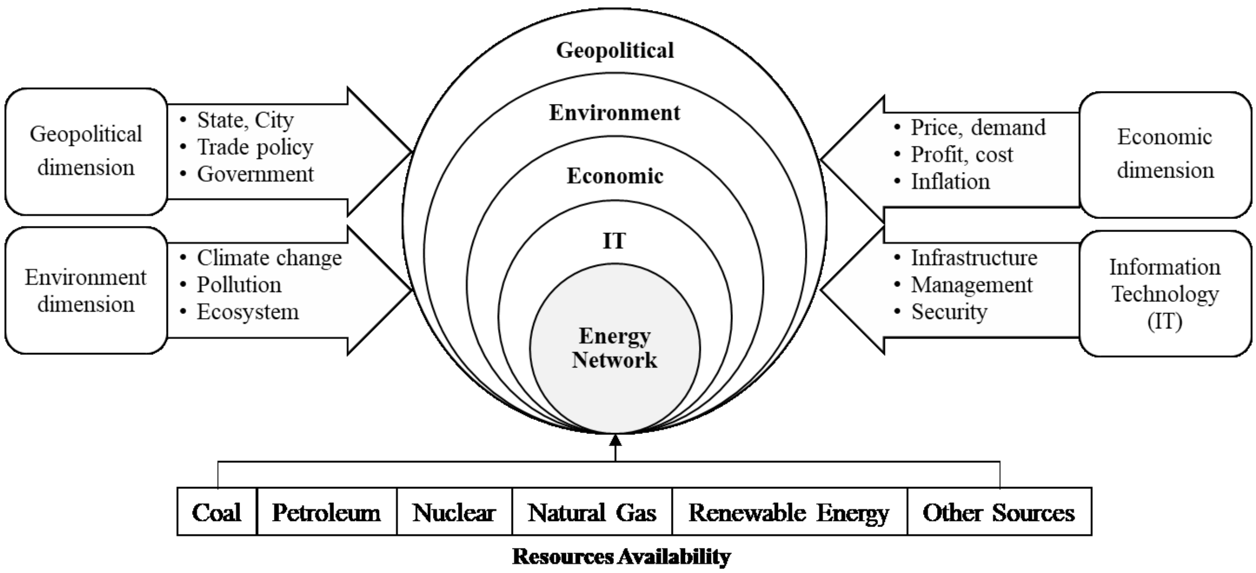

Figure 3: Multi-dimensional energy network influenced by multiple factors

Grijalva reviewed the multi-dimensional aspect of energy networks in modeling and analysis, optimization and control, and data management and visualization (Grijalva, 2017). Shaheen et al. proposed an advanced optimization algorithm called quasi-reflection jellyfish optimization for optimal energy management (Shaheen et al., 2022). The inherent large-scale of the overall energy infrastructure networks have made the holistic modeling and analysis of the multi-dimension energy network exponentially more complex and often impractical if combined. Thus, a multi-dimension energy network is often used when individually analyzing a specific dimension. Typically, this dimension is larger than the energy network itself, for example, poverty (Utami & Hartono, 2022) or security (Abdullah et al., 2022). However, some index-based approaches have been proposed to simplify the analysis of multiple dimensions of the energy network. Abdullah et al. optimize based on indicators such as price, reserves, governance, corruption, and consumption across five dimensions: affordability, availability, technology, government, and environment (Abdullah et al., 2022).

2.2 Vulnerabilities in Energy Infrastructure

Although complex characteristics of energy infrastructure discussed previously offer some advantages, such as improving energy supply reliability and minimizing dependency on non-renewable energy, the energy infrastructure is still vulnerable due to component failures, aging physical infrastructures, cyberattacks in the digital world, or natural disasters and climate change. Many U.S. energy infrastructure has been operating for over half a century, with some components perhaps over a century old (Rudin et al., 2011). Continuous usage without proper maintenance, component design, operating flaws, or typical wear and tear may cause a component failure in energy infrastructure. Depending on its importance measure, critical component failures may interrupt the operation of an energy network. An example of component failure commonly observed faults in a wind turbine is summarized in Table 1. Although some of the faults listed in Table 1 are typically deemed minor and do not usually cause a disruption in the entire network, the energy infrastructure system may still experience operational downtime due to unplanned maintenance.

Table 1: Common faults in wind turbine components (Hossain et al., 2018)

Components	Faults	Components	Faults
Gearbox	• Gear tooth abrasion • Tooth crack • Breakage • Facture	Rotor	• Fatigue, crack • Surface roughness • Asymmetries/ deformation • Reduced stiffness
Bearing	• Surface roughness • Fatigue • Crack, breakage • Outer/inner race • Ball and cage	Generator	• Fatigue, crack • Surface roughness • Asymmetries • Deformation • Reduced stiffness
Main shaft	• Corrosion • Crack, coupling failure • Misalignment	Blade	• Fatigue, crack • Detachment • Delamination

Components in the energy infrastructure networks are not only subjected to physical aging and failures. In this digital transformation era, energy infrastructure is often vulnerable to malicious cyberattacks. In 2021, the U.S. Colonial Pipeline ransomware affected numerous computerized pipeline management equipment. This incident resulted in a six-day shutdown of 5,500 miles of pipeline, which amounted to around 45% of fuel supplies on the East Coast (Paul, 2022). Due to the availability of internet connections worldwide that allows limited access to the digital world, cyberattacks will likely increase in frequency and intensity (Yodo & Goethals, 2019).

Climate change imposes vulnerability on energy infrastructure and impacts the availability of resources, supply, transmission, distribution, transfers, energy use, and physical infrastructure (Schaeffer et al., 2012). Component health deterioration, environmental factors, or other accidents can cause the components (nodes or links) in the overall energy network system to fail. Failures are not always observed in a particular component or nodes, but they can occur anywhere along the links, such as transmission lines or pipelines. Since energy infrastructure is highly connected, if the network is not designed correctly, a failure in either or both nodes and links components can cause overloading and eventually may result in cascading failure or collapse of the entire network (Afrin & Yodo, 2019b). A summary of different energy network characteristics and corresponding potential failures is presented in Table 2.

Table 2: Network characteristics and failures in energy infrastructure networks
(Ekic et al., 2022; Galvan & Agarwal, 2020; Liu & Song, 2020)

Network Type	Energy Type	Nodes	Links	Failure
Electric Power	Electrical	Buses; Generators	Transmission Lines; wires	• Extreme weathers • Cascading failures • Distribution failures

				• Transmission failures • Supply shortage • Planned outage for safety
Natural Gas	Chemical/ Thermal	Entry points; end-users; branches	Pipelines	• Technical failures • Pipeline failures • Systems and component failures • Extreme natural events • Accidents
Oil	Chemical/ Thermal	Storage tanks; processing facilities	Pipelines	• Mechanical • Corrosion • Operational • Natural hazards • Third-party failure
Heating	Thermal	Heat pump; Boilers; Consumers	Pipelines	• Material degradation • Pipeline failures • Corrosion • Extreme weathers

Energy infrastructure is vulnerable to unwanted failure risks that can cause minor or cascading failures (Galvan & Agarwal, 2020; Liu & Song, 2020). Cascading failure events will eventually become more frequent due to increasing energy demand coupled with deterioration or aging physical infrastructure. One recent example is the 2019 blackout in southeast South America involving three countries Argentina, Paraguay, and Uruguay (Yuan et al., 2019). During the regular maintenance activity, this incident was prompted by operational misbehavior while fixing the errored transmission lines tower. In the same year, 2019, Indonesia also suffers from a large-scale blackout across multiple islands from Java to Bali due to transmission disturbances (Praminta et al., 2020). The impact of this incident was widespread, causing disruptions in the telecommunication and transportation sector. Other occasions of power system cascading events can be found in various literature authored by Haes Alhelou et al. (Haes Alhelou et al., 2019) or Pushpa (Pushpa, 2019).

The frequency, duration, and intensity of natural disasters have increased over the years due to climate change and global warming (Van Aalst, 2006). The combination of severe natural disasters and energy infrastructure failures can be a life-threatening situation. Amid extreme weather disasters, energy infrastructure must continue to operate correctly to avoid more casualties. The current aging energy infrastructure is not entirely prepared for extreme-weather disasters (events like hurricanes, flooding, wildfires) and cyber-attacks, which are often inevitable due to their random and sudden occurrence. Therefore, there is an urgency to strengthen the current energy infrastructure with resilience strategies to develop disaster and climate resilience infrastructure energy systems. If resilience strategies are not integrated and appropriately applied, society will potentially experience more transmission lines and transformer failures, gas explosions, or pipeline ruptures.

2.3 Attributes of Resilient Energy Infrastructure

General engineering system resilience can be defined as the ability of a system to retain or resume its service level after a disruption (Adams et al., 2012). It is a quality that describes the ability of an energy infrastructure system to operate under exceptional conditions and the time it takes to restore to its previous state (Zorn & Shamseldin, 2015). In this context, resilience is an essential metric for system reliability and recovery following an attack or failure (Aydin et al., 2018; J. Wang & Liu, 2018).

According to C. Whitson et al., resilience is a combination of two fundamental attributes: (1) the system's ability to provide service despite external failures and (2) the time it takes to restore service when such failures occur (C. Whitson, 2009). Ouyang et al. defined system resilience as its ability to resist, prevent, and withstand potential disasters; absorb the initial damage, and restore normal functioning (Ouyang et al., 2012). Bruneau et al. described resilience as a comprehensive concept of three different aspects, including four dimensions (technical, organizational, social, and economic), four attributes (robustness, rapidity, redundancy, and resourcefulness), and three results (higher reliability, lower consequences, and faster recovery) (Bruneau et al., 2003).

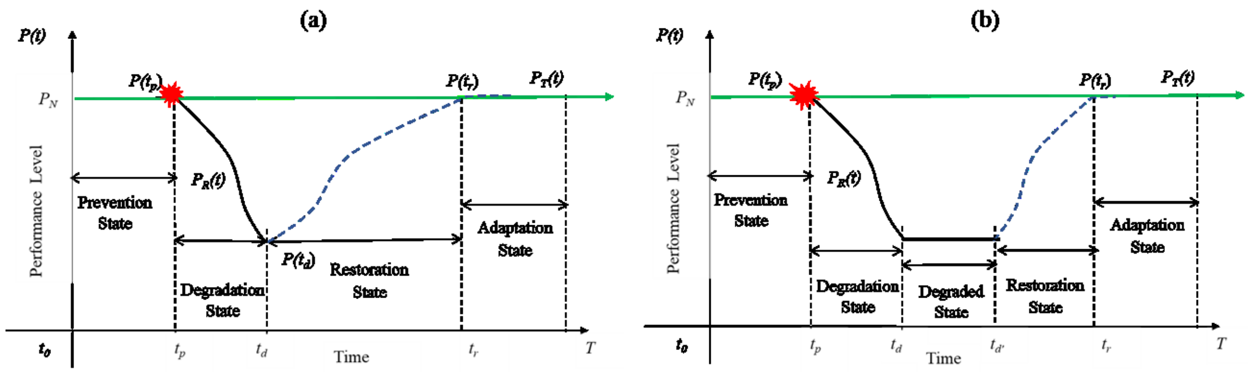

Figure 4: Performance of resilient energy infrastructure under extreme conditions
(a) without degraded state and (b) with the degraded state

The performance of infrastructure systems under an extreme event can be assessed in four states: prevention state, degradation state, restoration state, and adaptation state, as shown in Figure 4(a). The performance level and time are represented by the vertical and horizontal axes, respectively. The maximum attainable performance level is P_N, where the system operates at 100% capacity. The system performance in normal conditions before an extreme event occurs at time t_p is $P(t_p)$. This state is the prevention state as a short-term preparation can be taken here to mitigate the impact of the upcoming disaster. That is why condition-based maintenance can be implemented at this state to improve system resilience. At time t_p, an extreme event occurs that causes deterioration of the system's performance, denoted as $P_R(t)$, where *t*here is the time the system stays in the degradation states, often unknown but can be predicted (Yodo & Wang, 2018). The performance reaches an extreme point, $P(t_d)$ at time t_d. This transition of performance from normal to damaged condition is the degradation state. The degradation state demonstrates the impacts of the extreme event as well as the strength of the system. If the restoration process starts at this point, the pre-disaster performance level can be regained at time t_r. The degraded state will remain constant if no restoration efforts are taken, as shown in Figure 4(b).

The restoration state is the transition of the system's performance from the damaged condition to the pre-event condition. The system's performance improves gradually to P(tr) as the restoration procedures are executed. The applied restoration procedure is often assumed to regain 100% of system performance or at least a good portion of the system's functionality. The wholly or partially restored state is the adaptation state, where the system prepares for upcoming extreme events. In this state, the latest event can be evaluated to strengthen the system's ability to resist future disasters. That is why this state is also considered a long-term prevention state to achieve system sustainability (Afrin & Yodo, 2022a). In energy infrastructure applications, large-scale restoration practice must be as effective and efficient as possible, especially if the restoration needs to be completed promptly (Luo et al., 2021). This effective restoration practice often requires full knowledge of the system, which can be achieved through maintenance and monitoring efforts (Sun et al., 2022).

3. Resilience-oriented Condition-based Monitoring

Maintenance activities in energy infrastructure deal with reviving aging sub-systems or components, for example, upgrading decades-old transmission lines in a power grid (Hauser et al., 2005) or changing a wind turbine's damaged blade (Katsaprakakis et al., 2021). Some of these activities can be costly due to the rural locations, the complexity of the repairs, availability of spare components, or extended repair time. Many maintenance planning strategies have been applied to increase productivity and profitability, ensure availability and maintainability, enhance reliability and safety, and reduce overall costs and downtime risks in the energy industry (García Márquez, 2022). Potential failure events can be predicted through CBM, which helps decision makers take preventive or preplanned restorative actions and reduces the response and restoration time. Adaptively integrating CBM in the energy network can be one of the most effective approaches to enhancing holistic energy system resilience.

3.1 CBM Overview

Condition-based monitoring (CBM) is often referred to as a subset of predictive maintenance that uses sensors to monitor the health status of an asset over the operation time (Shin & Jun, 2015). CBM focuses on preventing asset failures, downtime, and maintenance cost by monitoring asset health to determine the type and time of maintenance. Being an essential part of predictive maintenance strategy, CBM aims to perform maintenance only when specific performance measures reach the thresholds indicating signs of deteriorating performance or upcoming potential failure (Achouch et al., 2022). A variety of sensors are installed in the system to gather various operational and performance data. Data analytics algorithms are then implemented to detect or predict the fault, which can help plan scheduled maintenance. An overview of CBM and the respective maintenance approach for an energy system is shown in Figure 5.

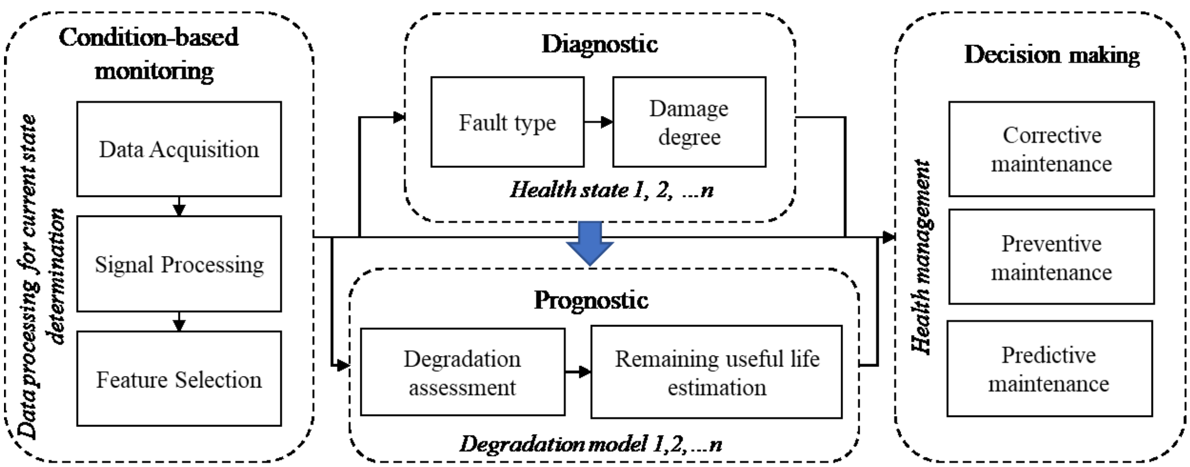

Figure 5: An overview of condition-based monitoring (CBM) and maintenance

The three critical steps of CBM include data acquisition, data/signal processing, and feature extraction (Tchakoua et al., 2014). Data acquisition does not compose only the on-site sensor or operation data. The data acquisition of prompt and reliable information on the health of infrastructure often includes multiple sources of data, such as visual inspections, non-destructive testing methods, or material coring (Abouhamad et al., 2017). Data collected through the sensors can be processed using different data processing algorithms. Additionally, data collected through inspections, testing, and coring can be inferred from various graphical representations and statistical analysis methods. From these processed data, parameter values are retrieved through the feature extraction process to establish the current status of the monitored system and to detect if there is any anomaly in the system. Fault detection and prediction, also known as diagnostic and prognostic, can be obtained after the data is processed. Further, depending on the failure conditions obtained, the decision makers should make an effective decision accordingly.

CBM has been employed for various purposes from evaluating different using behavior profiles for a particular equipment to hunting for outliers. CBM for diagnosis (fault detection) aims to identify a fault type and the degree of damage by differentiating healthy state and faulty conditions. The next step of fault diagnosis often results in corrective maintenance, where the maintenance occurs only after the fault or failure. There are two approaches for corrective maintenance, providing a temporary or provisional solution to the losses or seek for a more permanent or standing solution to the failures (Trojan & Marçal, 2016). CBM for prognosis (fault prediction) aims to predict future failures by learning current patterns in the signal data, assessing degradation models, and estimating the remaining useful life. Fault prediction is typically followed by preventive or predictive maintenance; both are performed before the actual fault of failure happens. There are four different approaches to preventive maintenance: scheduled maintenance (time-based), conditional maintenance (current-state-based), forecasting maintenance (projection-based), and proactive maintenance (status-based) (Tchakoua et al., 2014).

Components in energy infrastructure typically have different lifespans and criticality. Longer-lifespan components usually do not need to be monitored as frequently as shorter-lifespan components. Any critical components need to be observed as frequently as possible because the failure of critical components may cause deliberating impact on the overall energy infrastructure network. Based on the periodicity of the data collection for monitoring, CBM can be classified into three categories as follows.

- **Periodical monitoring:** Periodical monitoring is typically performed using a portable data logger with one or more sensors. The most used sensors are vibration and temperature sensors. Besides, a tachometer or stroboscope is used to measure a machine's rotation per minute (rpm). The collected data are stored at the data logger and uploaded to the maintenance server for further analysis. Depending on the potential failure characteristics and the cost-effectiveness, the commonly practiced periodicity for this type of condition monitoring is biweekly or monthly.
- **Semi-online monitoring:** The CBM process can be shifted to semi-online monitoring when running the periodical monitoring becomes difficult. The semi-online monitoring uses wireless sensors mounted on the machine body and automatically transfers the data to the maintenance server through a wireless connection. This type of monitoring is suitable for machines that work continuously at a relatively constant load. The commonly practiced periodicity for this type of condition monitoring is one data per day to check if there is any parameter that crosses the threshold limit.
- **Real-time, near real-time, or online monitoring:** When monitoring for a particular type of machine that works at variable load, does not work continuously, and a variety of process parameters need to be monitored, then the real-time monitoring system can be considered. The machine condition is constantly monitored, and an alarm is triggered when the health parameter reaches the threshold. In this type of condition monitoring, data is collected one time per hour or more. The data logger used for this application can recognize different sensor readings for various parameters, such as rpm, pressure, current, airflow, and others.

In energy infrastructure applications, common types of signal analysis in CBM include vibration monitoring and analysis, oil analysis, and temperature tracking/measurement (de Azevedo et al., 2016). However, other methods, including acoustic analysis, motor circuit testing, electrical monitoring, electromagnetic measurement, radiation analysis, and laser interferometry, are also used in CBM (Group, 2020). Specific sensors and measurement equipment are needed to collect the data for the respective analysis. These analyses and measurements that can be incorporated with CBM in energy infrastructure applications are further elaborated.

- **Vibration analysis:** The reaction of the system to vibration can reveal the time and area that requires maintenance. Vibrations caused by wear on parts can be examined to detect growing faults in rotational and structural components. Shock pulse analysis and wideband vibration analysis are two commonly used approaches used in vibration analysis.
- **Oil analysis:** Oil analysis is performed based on testing lubricants and other fluids. Both the fluid and the equipment can be analyzed for information. Wear particles, water pollution, viscosity, and other factors can be tested. Contaminants in lubricants and other fluids can indicate that a failure is imminent. Compressors, gearboxes, and the transportation industry are typical oil analysis applications.
- **Temperature measurements:** Different simple and complex approaches involving passive or active thermography are used for temperature-related analysis. Cameras used in thermography measure heat radiated by assets. These photos can be analyzed to indicate regions of probable failure. Excess heat or any thermal anomaly can be a sign of a problem, such as inadequate lubrication, worn parts, or misalignment.
- **Acoustic and ultrasonic analysis:** Acoustic analysis in maintenance can be classified into two types: sonic and ultrasonic. The sonic analysis is usually done with microphones and is used for lubrication analysis, such as detecting whether a piece of equipment is correctly lubricated. Ultrasonic analysis has a much broader range of applications. The ultrasonic analysis is beneficial in locations with a lot of background noise. Sensors can be designed to listen for a specific sound that indicates a probable failure, especially for the pitch range that is too high or too low for humans to hear. Leak detection, cavitation detection, and poorly seated parts are standard applications.
- **Motor circuit analysis:** The overall health of a motor is determined through motor circuit analysis. It should not be confused with motor current signature analysis, which focuses solely on ground resistance. Electrical imbalances and insulation degradation are the most typical reasons for motor failure. Thus, the motor relies on detecting them. Motor circuit analysis can be done online or offline, depending on whether the motor is running.
- **Electrical properties monitoring:** Electrical properties can occasionally be used to detect faults. This strategy frequently focuses on detecting electrical system degradation patterns to do preventative maintenance before the asset breaks. Induction, pulse and frequency response, capacitance, and resistance are some of the qualities that can be examined in this manner.
- **Electromagnetic measurement:** Electromagnetic measurements are used to discover problems by measuring distortions in the magnetic field and current variations. In essence, an electromagnetic field or current is induced inside or on the surfaces of the apparatus. The analysis will reveal which faults are generating problems in the electromagnetic field.
- **Radiation Analysis:** Radiation analysis uses radiation imaging to check assets and components. This can be one of the complete non-destructive testing methods. Radiation analysis examines the absorption rates of radiation in the material under investigation. Internal defects like rust may be invisible to the naked eye. On the other hand, these imperfections absorb different amounts of radiation, making them detectable.

- **Laser Interferometry:** Laser interferometers detect faults in numerous materials' surface and subsurface by measuring the displacement of two laser beams created by a beam splitter. There are two types of laser interferometers: amplitude-splitting and wave front-splitting.

Many other aspects of CBM are not discussed in detail in this paper due to the page limitation constraints. More information about CBM in energy infrastructure can be found in the cited literature (Blatter, 2021; de Azevedo et al., 2016; Group, 2020; Hossain et al., 2018; Shin & Jun, 2015; Stetco et al., 2019; Tchakoua et al., 2014).

3.2 CBM Impacts on Resilience

CBM is a robust strategy for preventive maintenance. CBM offers two fundamental advantages towards improving the overall resilience: (1) monitoring for fault prediction and detection allows for early detection of the potential fault type, potential occurrence time, and potential damage degree imposed. Therefore, (2) allowing more time for decision-making to determine the effective fault mitigation or restoration plan. Decision-makers also can draft additional contingency plans if the main plan did not turn out as expected due to implementation uncertainty. Thus, CBM is best implemented in the preventive state as a preventive strategy before the actual failure occurs. CBM also can be implemented during the restoration state to monitor restoration progress to ensure successful restoration is achieved. The best-case scenario of CBM in improving the overall resilience is presented in Figure 6, where early detection influences immediate restoration. Further, the overall system resilience can be enhanced by minimizing the potential performance loss.

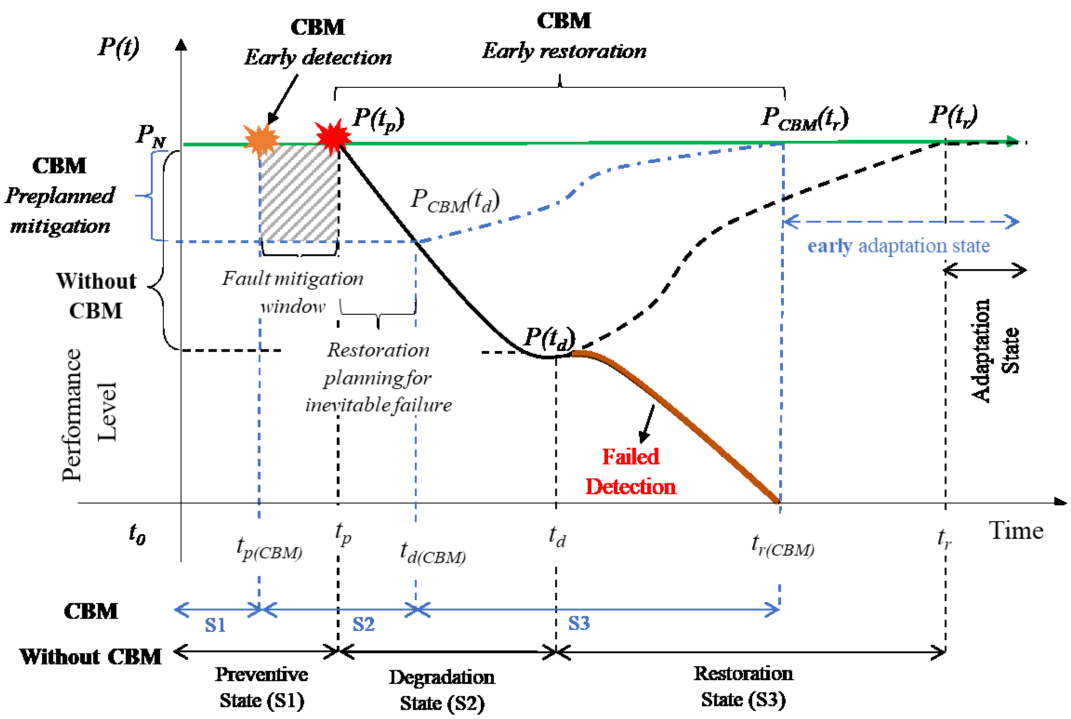

Figure 6: Best-case scenario of CBM impact on resilience

The time between early detection by CBM ($t_{p(CBM)}$) and actual occurrence (t_p) is the fault mitigation window. Depending on the severity of the actual failure, minor-degree failure may be resolved entirely, and the system can operate as usual without any disturbances. For a medium-degree loss, which may be inevitable, the decision makers can use the fault mitigation window to minimize the negative impact of the failure occurrence with a preplanned restoration planning. Thus, performance loss can be minimized from $P(t_d)$ to $P_{CBM}(t_d)$ with an early restoration executed at time $t_{d(CBM)}$ instead of at time t_d to subside further performance loss. With the early restoration plan in place, the restoration time required can be minimized from t_r to $t_{r(CBM)}$, and restoration state $P_{CBM}(t_r)$ can be completed in advance. For more severe failure losses that are often inevitable, for example, those included by a natural disaster, CBM implementation still allows for longer mitigation planning time from $t_{p(CBM)}$ to t_d, and shorter restoration time from t_d to $t_{r(CBM)}$, as shown in Figure 7.

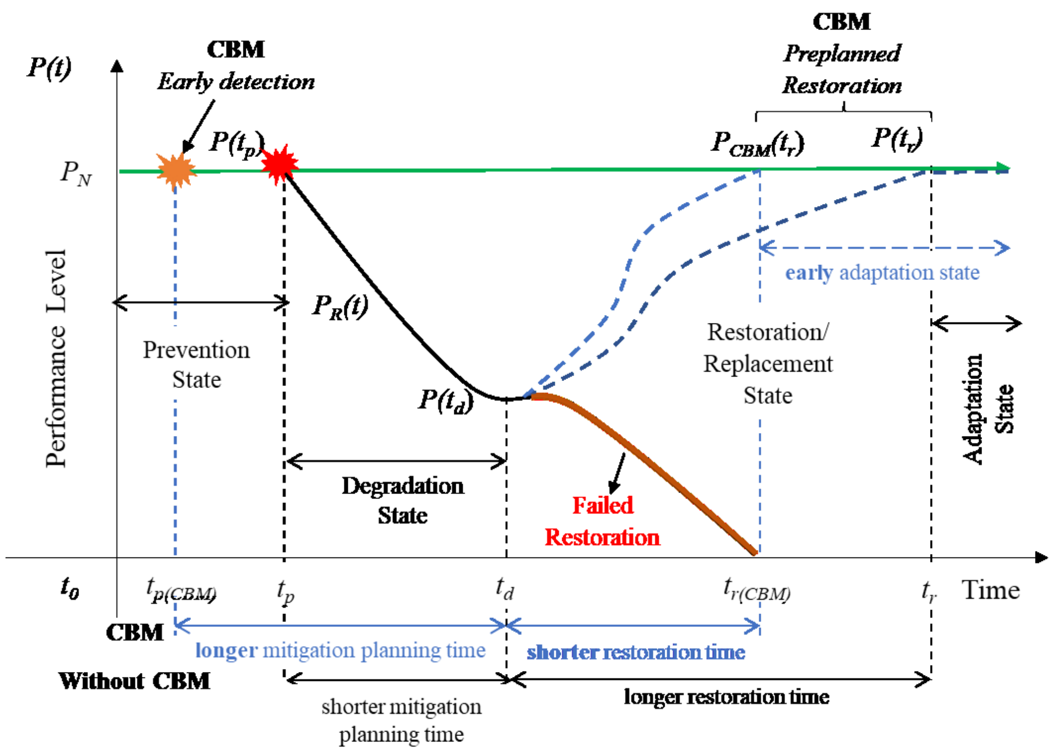

Figure 7: CBM impact on resilience for severe and inevitable failures

Additionally, some uncertainty risks that may lead to complete system failures, such as missed failure detections (Figure 6) or failed restoration executions (Figure 7), can be avoided by implementing CBM. As CBM can play a vital role in enhancing system resilience, simultaneously incorporating CBM and resilience quantification can help the system evaluation and effective decision-making process. Asadi et al. proposed a framework to integrate condition monitoring and resilience analysis for system modeling and control decision-making (Asadi et al., 2021). There is also a multidisciplinary approach to integrating CBM, control theory, dynamic system modeling, and resilience concept packaged in a control-guided failure restoration (CGFR) framework proposed to proactively restore loss performance promptly (Yodo & Wang, 2018). Therefore, CBM can be adaptively integrated to ensure failures are detected early, allows more time for mitigation and restoration planning, and minimizes restoration time in achieving overall energy infrastructure system resilience.

3.3 Data-driven Advances for CBM

As recent advancements in sensors, signal processing, and big data analytics significantly support improvement, machine learning (ML) and artificial intelligence (AI)-based data analysis approaches have taken over the old statistical techniques. The growing technological advancement and increasing computational capabilities have accelerated the integration of ML-based CBM analytics to differentiate various behavior or performance profiles or hunting for outliers. Besides, the application of ML can be a more reliable and cost-effective approach for robust decision-making in CBM (Khumprom & Yodo, 2019). ML algorithms learn the underlying patterns of a dataset and use that to understand the relationships in data. This learning can be supervised or unsupervised based on the available data structure. Supervised learning uses labeled input data to predict an output variable. On the other hand, unsupervised learning uses data without labeled inputs. The main steps of the ML process shown in Figure 8 are as follows (Afrin & Yodo, 2022b).

- **Data acquisition and preprocessing:** The required data for the analysis are collected through the data acquisition techniques. Different data sets can also be combined, and preprocessing should be performed. The preprocessing includes denoise the data, cleaning outliers, and normalizing the data.
- **Feature selection and extraction:** Significant features are selected and extracted from the raw data, and redundant information is removed. Commonly used feature selection methods include wrapper, embedded, and filter methods. Statistical attributes, fitting parameters, and domain properties are common feature extraction techniques.
- **Model selection:** In this step, an appropriate model is chosen considering the aim of the tasks, such as classification models for prediction and regression models for detection.
- **Model validation:** To evaluate and validate the models, different performance measures are used, such as accuracy, precision, mean absolute error, and root means square error.

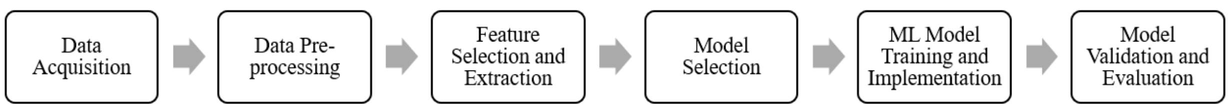

Figure 8: General flow chart for any general machine learning algorithm

A variety of fault detection and fault prediction models are available that can be used in CBM. Different categories of fault detection and prediction models are summarized in Figure 9. Fault detection or diagnosis models are mainly categorized as data-driven and knowledge-based models. The data-driven models include classification, regression, and unsupervised models. Support vector machine (SVM), principal component analysis (PCA), black-box model, and artificial neural network (ANN)-based models are the common data-driven models. The knowledge-based models include physical-based and rule-based models such as Bayesian networks, gray box models, and fuzzy logic-based models.

On the other hand, fault prediction or prognosis models can be categorized as data-driven, model-based, and physics-based models. Widely used data-driven models are SVM, hidden Markov model (HMM), and linear regression. In comparison, typical model-based approaches are Kalman-filtering and Particle filtering models. The physics-based models include Paris law and Taylor law in the general machine learning-based algorithm. The recent developments in CBM techniques mainly focus on AI-based data-driven models, such as ANN, long-short term memory (LSTM), SVM, linear regression, and others. Some of the recently developed machine learning approaches for CBM methods for energy infrastructure applications are summarized in Table 1. The same data-driven methods can be implemented for various applications for example ANN and SVM can be implemented for both fault diagnosis (Gangsar & Tiwari, 2020) and fault prognosis (Saravanan et al., 2020). Due to the limitation of the page, individual algorithms are not elaborated further.

It should be noted that even though AI or ML data analysis approaches hold multiple and valuable advantages for the infrastructure managers willing to exploit the immense amount of monitoring data to predict where and when future failures are most likely to occur, it is fundamental that readers and the practitioners have clear in mind that the correct application of these models is not so immediate and that there are still many open challenges. Some of these open challenges are discussed in the following section.

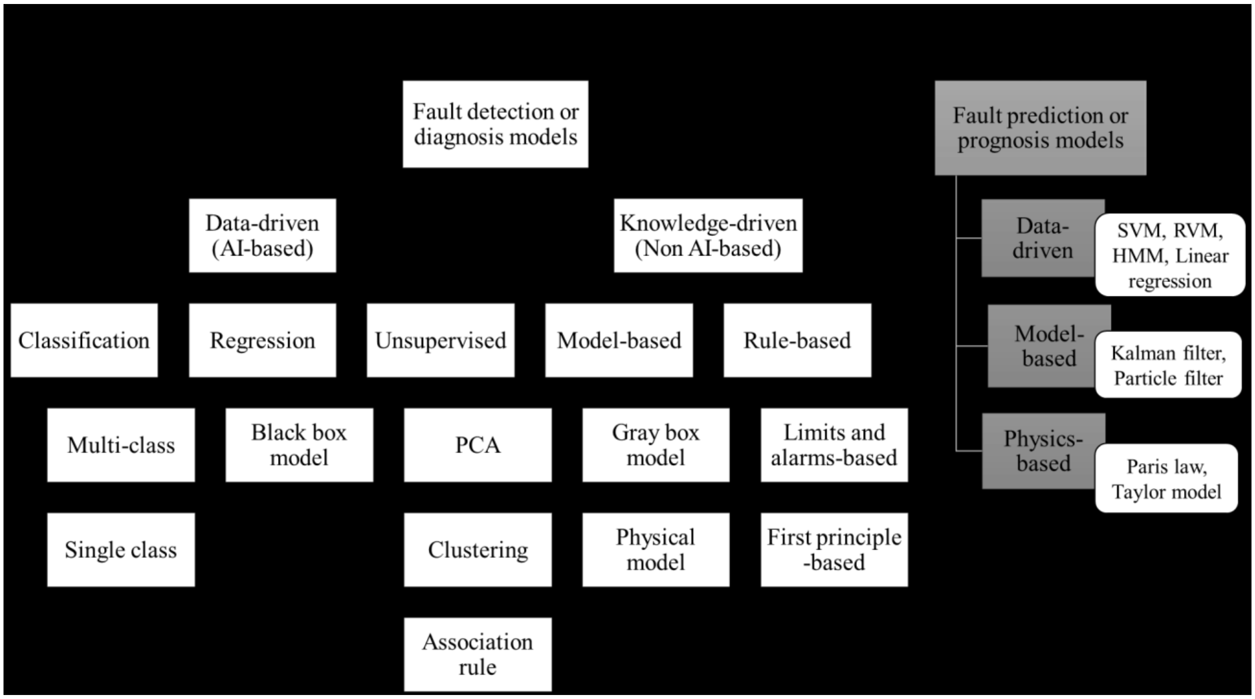

Figure 9: AI-based algorithm used for CBM diagnosis and prognosis adapted from (Jinjiang Wang et al., 2020; Zhao et al., 2019)

Table 1: Example of recently developed data-driven CBM approach in the energy sector

Reference	CBM	Method	Applications
(Chen et al., 2019)	Diagnosis	Deep residual network	Photovoltaic arrays
(Furse et al., 2020)	Diagnosis	High-frequency test methods and ML algorithms	Electrical wiring interconnection systems
(Gangsar & Tiwari, 2020)	Diagnosis	ANN, Fuzzy logic, SVM, and other hybrid AI-based methods	Induction motors
(Li et al., 2021)	Diagnosis	Artificial neural networks	Photovoltaic technology
(Xiang et al., 2021)	Diagnosis	CNN, LSTM	Wind turbine
(Zhang et al., 2022)	Diagnosis	Long short-term memory-based stacked denoising autoencoders (LSTM-SDAE), extreme gradient boosting (XGBoost)	Wind turbine
(Ahmad et al., 2018)	Prognosis	SVM, random forest, extra trees, regression trees	Solar thermal energy systems
(Saravanan et al., 2020)	Prognosis	Multilayer ANN, SVM	Power transformer
(Rashid et al., 2020)	Prognosis	Random forest, Adaptive boosting, K-neighbors	Wind turbine
(Betti et al., 2021)	Prognosis	Self-organizing map (SOM) neural network	Photovoltaic plants
(Skydt et al., 2021)	Prognosis	LSTM	Distribution grid

(Xiao et al., 2022)	Prognosis	Selective deep ensemble model: LSTM, CNN	Wind turbine blade icing

4. Discussion and Future Work

Many security policies, safety protocols, and other reliability efforts have been put in place to ensure the continuous supply of energy to support modern society and national interests. Energy infrastructure involving multi-energy sources, complex conversion and transmission operations, and a wide range of end-customer is defenseless to climate change in the physical world and cyberattacks in the digital world. The advantages of employing advanced CBM for early failure detection and efficient restoration planning are worth considering to be deployed extensively in energy infrastructure systems (Blatter, 2021).

Some of the most significant advantages of CBM include: (1) Minimize potential failure risks. Future system failure or component failures can be mitigated with CBM's early fault diagnosis and prognosis. Unscheduled downtime, maintenance time, and emergency replacement can be avoided completely or minimized with an effective mitigation plan. (2) Minimize performance loss in unavoidable failure scenarios or adverse failure impacts. CBM can identify failure properties which is beneficial for the decision makers to discover an effective mitigation and restoration plan. (3) Minimize costs of system failures, costs of restoration efforts, and costs of emergency responses. A head-of-failure detection allows decision-makers to refine and optimize any preplanned strategies. Therefore, the cost incurred after failures can be minimized with an optimal plan, optimal resources, and completion time. (4) Improve safety and reliability. With CBM, failure consequences can be reduced or eliminated altogether, and the degree of failures can be contained and not result in life-threatening failures. (5) Improve resilience. Putting together all the previous advantages, CBM can contribute to improving energy infrastructure resilience in predicting and responding to future risk and uncertainty.

The potential of the CBM approach being implemented in a larger-scale energy infrastructure application has grown in recent years with the development of advanced data-driven algorithms. These algorithms can minimize the data processing efforts to obtain a faster and more accurate prognosis and diagnosis results for the system. However, a few limitations of CBM need to be considered, and necessary steps must be taken before initiating the implementation. Some of these limitations include:

- Expensive test equipment and higher cost of data analysis for specific data collection
- Requirement of knowledgeable professional and skilled workers to develop and run the process
- Difficulty in detecting uniform wear failures, cascading failures impact, or other adverse failures
- Limitations of specific data availability or abundance of extensive data availability for prediction
- Requirement of overall physical and digital system modification to incorporate advanced CBM

Implementing CBM is a heavily data-driven process requiring sufficient good data to be used in the analysis. Although more variety of data can be gathered, this may or may not always result in better predictions. Generally, it was believed that with more data used in the analysis, the CBM prediction can be more reliable. However, due to various technology, knowledge, and policy constraints, only a few parameters can be gathered and used appropriately. The accuracy of the loosely employed CBM in various energy infrastructure domains needs to be verified due to the margin of prediction error inherent in all predictive approaches. Keeping the potentiality of error in mind, precautions must be taken before CBM is implemented extensively in large-scale energy infrastructure.

As sustainable energy supply is one of the most critical drivers for the nation’s industrial and economic growth, making current and future energy infrastructure more adaptable to disaster risks and resilient is essential. Some future research directions that can benefit this effort are:

1. **Assessment of hidden and complex interdependencies.** Increasing complexity in energy infrastructure also increases the vulnerabilities of not only energy infrastructure but also other critical infrastructure connected to the energy infrastructure. One area that can be explored further is the identification of hidden interdependencies between critical infrastructures, and quantifying the risk and economic impacts of these hidden interdependencies. AI/ML technologies can be implemented to harness the hidden interdependencies and potential vulnerabilities of multi-energy infrastructure systems. These interdependencies information will eventually benefit the CBM efforts in monitoring critical components within the system and external to the system.
2. **Decentralized framework with real-time data.** Another research direction is to develop a decentralized AI-based Internet of Things (IoT) architecture for heath monitoring and failure prediction systems, preferably with real-time data. It should be noted that gaining real-time data by itself is a challenge. Therefore, some advancements in IoT can be integrated with CBM efforts and AI/ML algorithms to develop a decentralized decision-making framework with real-time data capability. As decentralized framework often relies on cyberinfrastructure, security issues can be one of the challenges that should be addressed. Advances in cybersecurity and IoT security should also be integrated into the overall energy infrastructure systems to ensure sustainability and resiliency towards cyber risks.
3. **Robust decision-making framework to improve resilience**. As presented in Section 3.2, efficiently utilizing heterogeneous data obtained from CBM efforts can enhance resilience over three critical phases, pre-disaster, during a disaster, and post-disaster. The advancements of AI/ML can be adopted as enabling tools to learn from the situations and predict when the failure occurs and its impact. However, their potential has not been fully exploited to handle complex decision-making scenarios involving multiple layers, vectors, and dimensions of energy infrastructure. Another research direction is integrating advances in robust optimization efforts with the AI/ML-based CBM approach.

Although CBM and AI/ML are considered mature filed on their own, many opportunities exist to improve the future multidisciplinary integration of AI/ML and CBM to energy infrastructure resilience. Retrofitting new elements into existing infrastructure can be challenging, similarly to introducing innovative design elements to a new infrastructure. In addition to engineering and technological constraints, there are other dimensions; for example, the establishment of standard policy and security protocol can be further investigated as a potential future direction.

5. Conclusion

Any unexpected intrusion due to extreme weather, natural disasters, cyberattacks, or component failures can disrupt the energy infrastructure from functioning properly due to the complex characteristics of energy infrastructure. As it might not always be possible to avoid failures or prevent disaster risks, the aftermath of component failures and network restoration time can be minimized through CBM strategies. Integration of CBM before and after failure occurrence can significantly reduce performance loss and unwanted downtime and further improve system resilience. CBM can be applied to various energy infrastructures as a potential robust strategy against disaster risk and uncertainty. Although exemplary developments have been observed in the energy infrastructure sector, various challenges associated with large-scale integration of advanced CBM are laid out. Fusing advances in data-driven and CBM is believed to ease some of these associated challenges and eventually improve the energy infrastructure resilience against future extreme weather events.

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References

Abdullah, F. B., Iqbal, R., Ahmad, S., El-Affendi, M. A., & Kumar, P. (2022). Optimization of Multidimensional Energy Security: An Index Based Assessment. *Energies*, *15*(11), 3929.

Abeysekera, M. (2016). *Combined analysis of coupled energy networks*, Cardiff University].

Abouhamad, M., Dawood, T., Jabri, A., Alsharqawi, M., & Zayed, T. (2017). Corrosiveness mapping of bridge decks using image-based analysis of GPR data. *Automation in Construction*, *80*, 104-117.

Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Applied Sciences*, *12*(16), 8081.

Adams, T. M., Bekkem, K. R., & Toledo-Durán, E. J. J. J. o. T. E. (2012). Freight resilience measures. *138*(11), 1403-1409.

Afrin, T., & Yodo, N. (2019). A concise survey of advancements in recovery strategies for resilient complex networks. *Journal of Complex Networks*, *7*(3), 393-420.

Afrin, T., & Yodo, N. (2022a). A Hybrid Recovery Strategy toward Sustainable Infrastructure Systems. *Journal of Infrastructure Systems*, *28*(1), 04021054.

Afrin, T., & Yodo, N. (2022b). A Long Short-Term Memory-based correlated traffic data prediction framework. *Knowledge-Based Systems*, *237*, 107755.

Ahmad, M. W., Reynolds, J., & Rezgui, Y. (2018). Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees. *Journal of cleaner production*, *203*, 810-821.

Asadi, E., Salman, A. M., Li, Y., & Yu, X. (2021). Localized health monitoring for seismic resilience quantification and safety evaluation of smart structures. *Structural Safety*, *93*, 102127.

Aydin, N. Y., Duzgun, H. S., Heinimann, H. R., Wenzel, F., & Gnyawali, K. R. (2018). Framework for improving the resilience and recovery of transportation networks under geohazard risks. *International Journal of Disaster Risk Reduction*.

Ayyub, B. M. (2015). Practical resilience metrics for planning, design, and decision making. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *1*(3), 04015008.

Ayyub, B. M. (2020). Infrastructure resilience and sustainability: Definitions and relationships. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *6*(3), 02520001.

Bagherian, M. A., Mehranzamir, K., Pour, A. B., Rezania, S., Taghavi, E., Nabipour-Afrouzi, H., Dalvi-Esfahani, M., & Alizadeh, S. M. (2021). Classification and Analysis of Optimization Techniques for Integrated Energy Systems Utilizing Renewable Energy Sources: A Review for CHP and CCHP Systems. *Processes*, *9*(2), 339.

Betti, A., Tucci, M., Crisostomi, E., Piazzi, A., Barmada, S., & Thomopulos, D. (2021). Fault prediction and early-detection in large pv power plants based on self-organizing maps. *Sensors*, *21*(5), 1687.

Bhattacharyya, S. C. (2019). *Energy economics: concepts, issues, markets and governance*. Springer Nature.

Blatter, B. (2021). *Condition-Based Monitoring: The Future of Machine Maintenance* itiretailservices.citibankonline.com/RSnextgen/svc/launch/index.action?siteId=PLCN_BESTBUY&langId=en_US&pagename=authenticate#dashboard

Blondeel, M., Bradshaw, M. J., Bridge, G., & Kuzemko, C. (2021). The geopolitics of energy system transformation: A review. *Geography Compass*, *15*(7), e12580.

Bruckner, T., Bashmakov, I. A., Mulugetta, Y., Chum, H., De la Vega Navarro, A., Edmonds, J., Faaij, A., Fungtammasan, B., Garg, A., & Hertwich, E. (2014). Energy systems.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & Winterfeldt, D. V. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, *19*, 733–752.

Busby, J. W., Baker, K., Bazilian, M. D., Gilbert, A. Q., Grubert, E., Rai, V., Rhodes, J. D., Shidore, S., Smith, C. A., & Webber, M. E. (2021). Cascading risks: Understanding the 2021 winter blackout in Texas. *Energy Research & Social Science*, *77*, 102106.

C. Whitson, J., Ramirez-Marquez, J. E. (2009). Resiliency as a component importance measure in network reliability. *Reliability Engineering and System Safety*, 94(1685-1693).

Carradore, L., & Turri, R. (2009). Modeling and simulation of multi-vector energy systems. (Ed.),^(Eds.). 2009 IEEE Bucharest PowerTech.

Chauhan, A., & Saini, R. (2014). A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control. *Renewable and Sustainable Energy Reviews*, *38*, 99-120.

Chen, Z., Chen, Y., Wu, L., Cheng, S., & Lin, P. (2019). Deep residual network based fault detection and diagnosis of photovoltaic arrays using current-voltage curves and ambient conditions. *Energy Conversion and Management*, *198*, 111793.

Cohen, A. (2021a). *Hurricane Ida Puts America's Energy Security To The Test*. Forbes https://www.forbes.com/sites/arielcohen/2021/09/01/hurricane-ida-puts-americas-energy-security-to-the-test/?sh=18fdd3d24c99

Cohen, A. (2021b). *Texas Energy Crisis Is An Epic Resilience And Leadership Failure*. Forbes https://www.forbes.com/sites/arielcohen/2021/02/19/texas-energy-crisis-is-an-epic-resilience-and-leadership-failure/?sh=3eb05e546eee

Davoudi, M., Jooshaki, M., Moeini-Aghtaie, M., Barmayoon, M. H., & Aien, M. (2022). Developing a multi-objective multi-layer model for optimal design of residential complex energy systems. *International Journal of Electrical Power & Energy Systems*, *138*, 107889.

de Azevedo, H. D. M., Araújo, A. M., & Bouchonneau, N. (2016). A review of wind turbine bearing condition monitoring: State of the art and challenges. *Renewable and Sustainable Energy Reviews*, *56*, 368-379.

Ekic, A., Wu, D., & Huang, Y. (2022). A Review on Cascading Failure Analysis for Integrated Power and Gas Systems. (Ed.),^(Eds.). 2022 IEEE 7th International Energy Conference (ENERGYCON).

Furse, C. M., Kafal, M., Razzaghi, R., & Shin, Y.-J. (2020). Fault diagnosis for electrical systems and power networks: A review. *IEEE Sensors Journal*, *21*(2), 888-906.

Galvan, G., & Agarwal, J. (2020). Assessing the vulnerability of infrastructure networks based on distribution measures. *Reliability Engineering & System Safety*, *196*, 106743.

Gangsar, P., & Tiwari, R. (2020). Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. *Mechanical systems and signal processing*, *144*, 106908.

García Márquez, F. P. (2022). Special Issue on Advances in Maintenance Management (Vol. 15, pp. 2499). MDPI.

Geman, B., & Freedman, A. (2021). *Hurricane Ida exposes America's precarious energy infrastructure*. Axios

Goswami, D. Y., & Kreith, F. (2007). *Energy conversion*. CRC press.

Grijalva, S. (2017). Multi-Dimensional, Multi-Scale Modeling and Algorithms for Integrating Variable Energy Resources in Power Networks: Challenges and Opportunities. *Renewable Energy Integration*, 41-53.

Group, P. (2020). The Importance of Condition Based Monitoring.

Haes Alhelou, H., Hamedani-Golshan, M. E., Njenda, T. C., & Siano, P. (2019). A survey on power system blackout and cascading events: Research motivations and challenges. *Energies*, *12*(4), 682.

Hauser, C. H., Bakken, D. E., & Bose, A. (2005). A failure to communicate: next generation communication requirements, technologies, and architecture for the electric power grid. *IEEE Power and Energy Magazine*, *3*(2), 47-55.

Hossain, M. L., Abu-Siada, A., & Muyeen, S. (2018). Methods for advanced wind turbine condition monitoring and early diagnosis: A literature review. *Energies*, *11*(5), 1309.

Hosseini, S. H. R., Allahham, A., Vahidinasab, V., Walker, S. L., & Taylor, P. (2021). Techno-economic-environmental evaluation framework for integrated gas and electricity distribution networks considering impact of different storage configurations. *International Journal of Electrical Power & Energy Systems*, *125*, 106481.

Hosseini, S. H. R., Allahham, A., Walker, S. L., & Taylor, P. (2020). Optimal planning and operation of multi-vector energy networks: A systematic review. *Renewable and Sustainable Energy Reviews*, *133*, 110216.

Karad, S., & Thakur, R. (2021). Efficient monitoring and control of wind energy conversion systems using Internet of things (IoT): a comprehensive review. *Environment, development and sustainability*, *23*(10), 14197-14214.

Katsaprakakis, D. A., Papadakis, N., & Ntintakis, I. (2021). A comprehensive analysis of wind turbine blade damage. *Energies*, *14*(18), 5974.

Khumprom, P., & Yodo, N. (2019). A data-driven predictive prognostic model for lithium-ion batteries based on a deep learning algorithm. *Energies*, *12*(4), 660.

Li, B., Delpha, C., Diallo, D., & Migan-Dubois, A. (2021). Application of Artificial Neural Networks to photovoltaic fault detection and diagnosis: A review. *Renewable and Sustainable Energy Reviews*, *138*, 110512.

Liu, W., & Song, Z. (2020). Review of studies on the resilience of urban critical infrastructure networks. *Reliability Engineering & System Safety*, *193*, 106617.

Lombardi, F., Rocco, M. V., & Colombo, E. (2019). A multi-layer energy modelling methodology to assess the impact of heat-electricity integration strategies: The case of the residential cooking sector in Italy. *Energy*, *170*, 1249-1260.

Lounis, Z., & McAllister, T. P. (2016). Risk-based decision making for sustainable and resilient infrastructure systems. *Journal of Structural Engineering*, *142*(9), F4016005.

Luo, H., Alkhaleel, B. A., Liao, H., & Pascual, R. (2021). Resilience improvement of a critical infrastructure via optimal replacement and reordering of critical components. *Sustainable and Resilient Infrastructure*, *6*(1-2), 73-93.

Min, Z., Muqing, W., Lilin, Q., Quanbiao, A., & Sixu, L. (2021). Evaluation of Cross-Layer Network Vulnerability of Power Communication Network Based on Multi-Dimensional and Multi-Layer Node Importance Analysis. *IEEE Access*, *10*, 67181-67197.

Mosheiov, G., & Sarig, A. (2009). Scheduling a maintenance activity to minimize total weighted completion-time. *Computers & Mathematics with Applications*, *57*(4), 619-623.

Nazari-heris, M., Jabari, F., Mohammadi-ivatloo, B., Asadi, S., & Habibnezhad, M. (2020). An updated review on multi-carrier energy systems with electricity, gas, and water energy sources. *Journal of Cleaner Production*, *275*, 123136.

O'Malley, M. J., Anwar, M. B., Heinen, S., Kober, T., McCalley, J., McPherson, M., Muratori, M., Orths, A., Ruth, M., & Schmidt, T. J. (2020). Multicarrier energy systems: shaping our energy future. *Proceedings of the IEEE*, *108*(9), 1437-1456.

Ouyang, M., Dueñas-Osorio, L., & Min, X. (2012). A three-stage resilience analysis framework for urban infrastructure systems. *Structural Safety*, *36*, 23-31.

Paul, L. (2022). Oil and Gas Pipeline Cybersecurity. *Tex. J. Oil Gas & Energy L.*, *17*, 38.

Praminta, S. M., Wiguna, S., & Pramana, A. (2020). Blackout Restoration Plan in Jakarta Power Grid. (Ed.),^(Eds.). 2020 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP).

Pushpa, S. (2019). Major Blackouts in The World and Lessons Learned. *Water and Energy International*, *62*(5), 28-34.

Rashid, H., Khalaji, E., Rasheed, J., & Batunlu, C. (2020). Fault Prediction of Wind Turbine Gearbox Based on SCADA Data and Machine Learning. (Ed.),^(Eds.). 2020 10th International Conference on Advanced Computer Information Technologies (ACIT).

Renugadevi, N., Saravanan, S., & Sudha, C. N. (2021). IoT based smart energy grid for sustainable cites. *Materials Today: Proceedings*.

Reynolds, J., Ahmad, M. W., & Rezgui, Y. (2018). Holistic modelling techniques for the operational optimisation of multi-vector energy systems. *Energy and Buildings*, *169*, 397-416.

Rudin, C., Waltz, D., Anderson, R. N., Boulanger, A., Salleb-Aouissi, A., Chow, M., Dutta, H., Gross, P. N., Huang, B., & Ierome, S. (2011). Machine learning for the New York City power grid. *IEEE transactions on pattern analysis and machine intelligence*, *34*(2), 328-345.

Samsatli, S., & Samsatli, N. J. (2018). A multi-objective MILP model for the design and operation of future integrated multi-vector energy networks capturing detailed spatio-temporal dependencies. *Applied Energy*, *220*, 893-920.

Saravanan, D., Hasan, A., Singh, A., Mansoor, H., & Shaw, R. N. (2020). Fault prediction of transformer using machine learning and DGA. (Ed.),^(Eds.). 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON).

Schaeffer, R., Szklo, A. S., de Lucena, A. F. P., Borba, B. S. M. C., Nogueira, L. P. P., Fleming, F. P., Troccoli, A., Harrison, M., & Boulahya, M. S. (2012). Energy sector vulnerability to climate change: A review. *Energy*, *38*(1), 1-12.

Shafie-Khah, M., & Catalão, J. P. (2014). A stochastic multi-layer agent-based model to study electricity market participants behavior. *IEEE Transactions on Power Systems*, *30*(2), 867-881.

Shaheen, A. M., Elsayed, A. M., El-Sehiemy, R. A., Ghoneim, S. S., Alharthi, M. M., & Ginidi, A. R. (2022). Multi-dimensional energy management based on an optimal power flow model using an improved quasi-reflection jellyfish optimization algorithm. *Engineering Optimization*, 1-23.

Shin, J.-H., & Jun, H.-B. (2015). On condition based maintenance policy. *Journal of Computational Design and Engineering*, *2*(2), 119-127.

Skydt, M. R., Bang, M., & Shaker, H. R. (2021). A probabilistic sequence classification approach for early fault prediction in distribution grids using long short-term memory neural networks. *Measurement*, *170*, 108691.

Stetco, A., Dinmohammadi, F., Zhao, X., Robu, V., Flynn, D., Barnes, M., Keane, J., & Nenadic, G. (2019). Machine learning methods for wind turbine condition monitoring: A review. *Renewable energy*, *133*, 620-635.

Sun, H., Yang, M., & Wang, H. (2022). Resilience-based approach to maintenance asset and operational cost planning. *Process Safety and Environmental Protection*, *162*, 987-997.

Taylor, P., Abeysekera, M., Bian, Y., Ćetenović, D., Deakin, M., Ehsan, A., Levi, V., Li, F., Oduro, R., & Preece, R. (2022). An interdisciplinary research perspective on the future of multi-vector energy networks. *International Journal of Electrical Power & Energy Systems*, *135*, 107492.

Tchakoua, P., Wamkeue, R., Ouhrouche, M., Slaoui-Hasnaoui, F., Tameghe, T. A., & Ekemb, G. (2014). Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges. *Energies*, *7*(4), 2595-2630.

Trojan, F., & Marçal, R. (2016). Sorting maintenance types by multi-criteria analysis to clarify maintenance concepts in POM. (Ed.),^(Eds.). Production and Operations Management Society 27th Annual Conference.

U.S. Energy Information Administration. (2022). U.S. energy facts explained: The United States uses a mix of energy sources https://www.eia.gov/energyexplained/us-energy-facts/

Utami, C. N., & Hartono, D. (2022). A Multidimensional Energy Poverty in Indonesia and Its Impact on Health. *International Energy Journal*, *22*(2).

Van Aalst, M. K. (2006). The impacts of climate change on the risk of natural disasters. *Disasters*, *30*(1), 5-18.

Wang, J., Liang, Y., Zheng, Y., Gao, R. X., & Zhang, F. (2020). An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples. *Renewable energy*, *145*, 642-650.

Wang, J., & Liu, H. (2018). Snow removal resource location and allocation optimization for urban road network recovery: a resilience perspective. *Journal of Ambient Intelligence and Humanized Computing*.

Wen, M., Chen, Y., Yang, Y., Kang, R., & Zhang, Y. (2020). Resilience-based component importance measures. *International Journal of Robust and Nonlinear Control*, *30*(11), 4244-4254.

Wohlin, C., Kalinowski, M., Felizardo, K. R., & Mendes, E. (2022). Successful combination of database search and snowballing for identification of primary studies in systematic literature studies. *Information and Software Technology*, *147*, 106908.

Wu, J., & Wang, P. (2021). Post-disruption performance recovery to enhance resilience of interconnected network systems. *Sustainable and Resilient Infrastructure*, *6*(1-2), 107-123.

Xiang, L., Wang, P., Yang, X., Hu, A., & Su, H. (2021). Fault detection of wind turbine based on SCADA data analysis using CNN and LSTM with attention mechanism. *Measurement*, *175*, 109094.

Xiao, J., Li, C., Liu, B., Huang, J., & Xie, L. (2022). Prediction of wind turbine blade icing fault based on selective deep ensemble model. *Knowledge-Based Systems*, *242*, 108290.

Yang, S.-l., Ma, Y., Xu, D.-l., & Yang, J.-b. (2011). Minimizing total completion time on a single machine with a flexible maintenance activity. *Computers & Operations Research*, *38*(4), 755-770.

Yodo, N., & Goethals, P. L. (2019). Cybersecurity Management via Control Strategies for Resilient Cyber-Physical Systems. (Ed.),^(Eds.). IIE Annual Conference. Proceedings.

Yodo, N., & Wang, P. (2016). Engineering Resilience Quantification and System Design Implications: A literature Survey. *Journal of Mechanical Design*, *138*(111408), 1-13.

Yodo, N., & Wang, P. (2018). A control-guided failure restoration framework for the design of resilient engineering systems. *Reliability Engineering & System Safety*, *178*, 179-190.

Yodo, N., Wang, P., & Rafi, M. (2017). Enabling resilience of complex engineered systems using control theory. *IEEE Transactions on Reliability*, *67*(1), 53-65.

Yuan, P., Zhang, Q., Zhang, T., Chi, C., Zhang, X., Li, P., & Gong, X. (2019). Analysis and enlightenment of the blackouts in Argentina and New York. (Ed.),^(Eds.). 2019 Chinese Automation Congress (CAC).

Zhang, C., Hu, D., & Yang, T. (2022). Anomaly detection and diagnosis for wind turbines using long short-term memory-based stacked denoising autoencoders and XGBoost. *Reliability Engineering & System Safety*, *222*, 108445.

Zhao, Y., Li, T., Zhang, X., & Zhang, C. (2019). Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future. *Renewable and Sustainable Energy Reviews*, *109*, 85-101.

Zorn, C. R., & Shamseldin, A. Y. (2015). Post-disaster infrastructure restoration: A comparison of events for future planning. *International Journal of Disaster Risk Reduction*, *13*, 158-166.